The Effects of US State Policy on the COVID19 Beta Transmission Rate

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1 Abstract

The development of 'social distancing' since the outbreak of COVID19 in the US has been a prominent and important ideal to slowing COVID19 spread. Social distancing has certainly manifested itself as both a social construct that has grown concurrently with the spread of COVID in the US, but has also been a large aspect of governmental policy implementation since early February. Many states have seen indefinite, statewide stay-at-home policies and business closures that many argue have extremely detrimental effects on the US economy and unemployment rates. The cost of such nationwide policies is seen by many as too high, as many businesses both small and large are troubled with potential bankruptcy and many individuals find themselves unemployed just a few months into the COVID outbreak. This raises questions of how beneficial such policies are to slowing COVID spread. As we see many states beginning to end their closures and many individuals beginning to end social distancing, especially in the context of the recent nationwide protests, many additional questions arise. How much have state policies slowed COVID spread thus far? How will different rates of distancing and different levels of restrictive policy result in different curves of COVID spread for the US in the next three months? How do social distancing policies affect the size, probability, and timeline of a COVID 'second wave' in the US? This paper aims to answer these questions, and explore the effects of policy on the US COVID pandemic.

2 Data Sets

A Brief Description of Data Sets used:

- BU State Coronavirus Policy Dataset A dataset of policies for business closure, stay-at-home orders, etc. for all US states and districts published by Boston University and updated weekly. It was used to track the number of states with precautions taken and policies implemented (1)
- CTP US COVID History Dataset A dataset published by The Covid Tracking Project that is updated daily the number of cumulative, daily, positive, negative, hospitalized etc cases per day (2)
- CTP Current US State COVID19 Data A dataset updated daily and also published by The Covid Tracking Project that records the severity, number, and type of cases in each state (2)

3 Introduction

Since the beginning of the global COVID19 crisis, the SIR model has stood as one of the staple epidemiological models for predicting disease spread and, consequently, for policy implementation. Its relative simplicity makes it both practical and straightforward, as it only implements two parameters: the inverse of the number of days that an infected individual can spread the disease (γ rate) and the number of interactions an average individual has on a daily basis that are viable to spread disease (β infection rate). While modeling policy and social distancing, γ is relatively consistent as it is correlated with the incubation period of the disease, which is biological and independent of social reform. On the other hand, β varies largely as different distancing policies are implemented as it is directly correlated with social factors. Consequently, for our purposes of studying the effects of state policy on COVID19 spread and its potential future spread, we will focus on exclusively modeling the β transmission rate with respect to different periods and levels of US policy implementation. Moreover, to answer questions regarding the future spread of COVID19, we will use these modeled β transmission values to predict how severe COVID19 will be in the US depending on the level of distancing and state policy implemented during the coming months.

4 National COVID19 Policies: A Timeline

For the purposes of this paper, and for the sake of simplicity, we will explore the effects of specifically mandatory stay-at-home orders and mandatory business closures in US states. While there are certainly other types of policies that have been implemented to encourage distancing, these variables should sufficiently reflect governmental efforts to enforce social distancing and, additionally, should have a significant effect on transmission rate over time during the pandemic. Statewide policies for stay-at-home orders and mandatory non-essential business closures began around 50 days after the first recorded case of COVID, which was discovered on January 22 2020(1). Now, only around two months later, a large majority of states have neglected their COVID distancing policies. The two figures on the following page show the duration of stay-at-home and business closure policies in the US states.

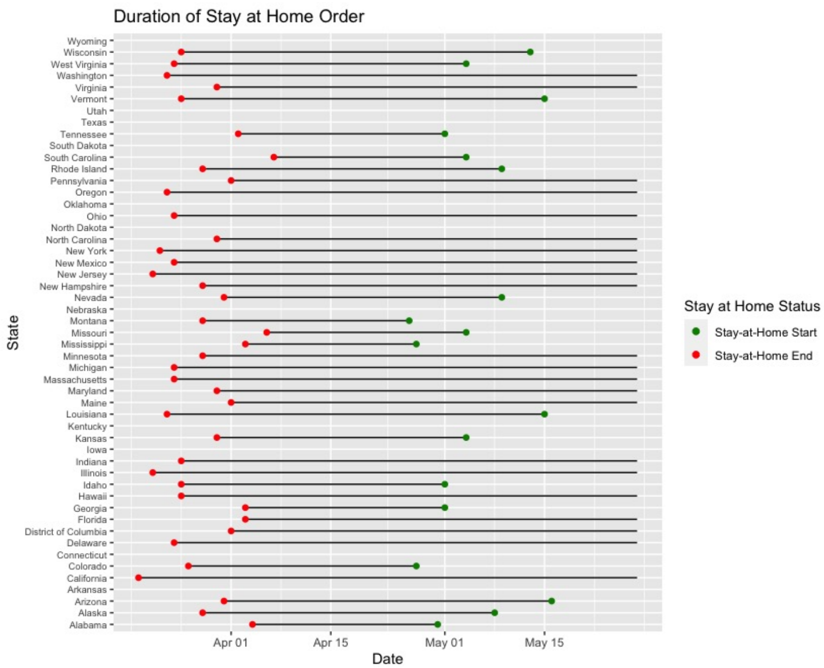

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Figure 1: State Stay-At-Home Order

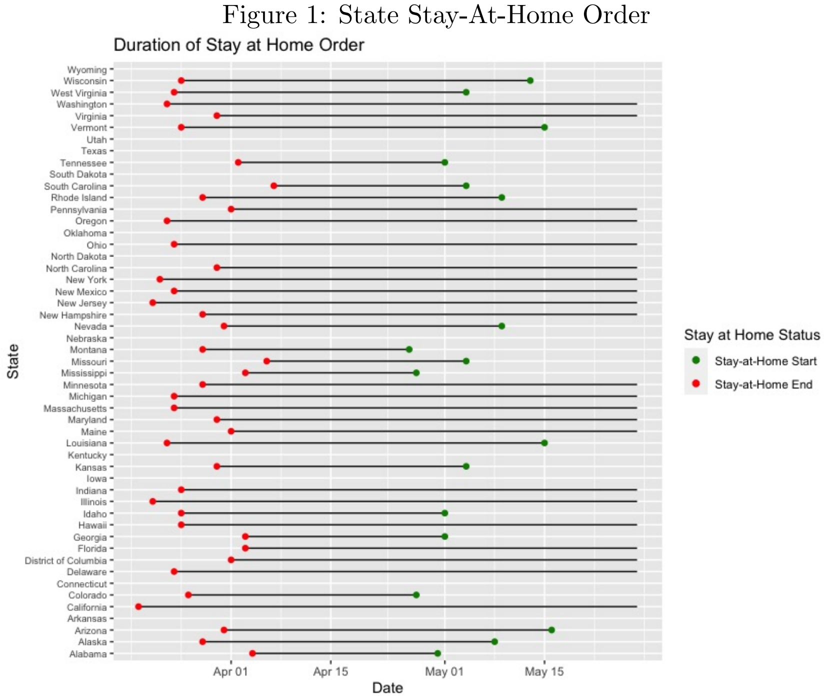

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Figure 2: State Closed Non-Essential Business Order

From these figures, one can easily tell that state stay-at-home policies occur somewhat simultaneously with mandatory non-essential business closures. In other words, the time periods where stay-at-home orders are in place are congruent with the time periods where business closures are in place. This is almost universally true, except for very recently as there have been more business openings than stay-at-home terminations over the past thirty or so days. This is majorly because of the economic pressures to open businesses due to spiking unemployment rates. The relationship between closed business rates and stay-at-home orders nationally can be interpreted more thoroughly in the figure below.

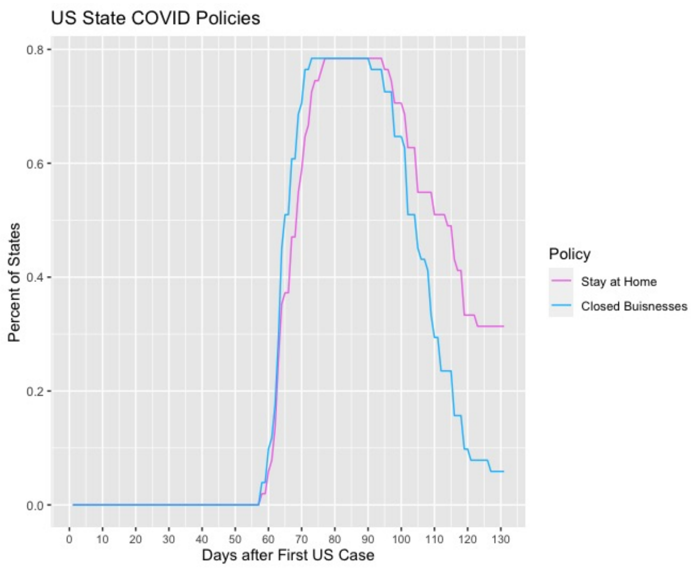

Figure 3: Percent of States with Distancing Policies Over Time

All of this information is useful in our study, as we can use similar time periods over the past three months to represent both high percents of state stay-at-home implementation with high state mandatory business closures. To best take advantage of the simultaneous occurrence of these two types of policies, throughout the rest of this paper we will consider 'percent of states with stay-at-home order' and 'percent of states with closed non-essential businesses' more generally as 'percent of states with policy implementation.' Moreover, to study change in transmission rate over time, we will use the following time periods to represent respective levels of policy. Note that the final two time periods are reflections of both current transmission rates and are a bi-product of months of policy implementation, which as we see in the figure above is being gradually discontinued by states across the US. For each of these periods, we will fit US COVID data with a SIR model to approximate β infection rates.

- Day 1-60 0% of States with Policy Implementation
- Day 75-95 80% of States with Policy Implementation
- Day 100-140 Last 40 Days
- Day 130-140 Last 10 Days

5 Modeling β Infection Rates for Different Levels of US State Policy Implementation

Recall that the SIR model has the following outputs and parameters.

- N Total Population
- S(t) Number of people susceptible on day t
- I(t) Number of people infected on day t
- R(t) Number of people Recovered on day t
- β The average number of close contacts of a person per day
- γ The inverse of the number of days an infected person can spread the disease

As stated in the introduction, the γ parameter should not vary much with time or with different levels of distancing because it is biological and dependent on the characteristics of COVID as a disease (ie. not on how society manages the pandemic). For this reason, and because for the purposes of this paper we are not interested in its effect, it is beneficial to fix γ to a commonly reported value. Recall that $\gamma = \frac{1}{D_i}$ where,

$$D_i = \textit{(Number of days an infected person can spread the disease)}.$$

According to many public health sources, as cited below, 0.2 is a highly reported to be the center of confidence intervals for γ. This simply means a person spread COVID for an average of 5 days before self isolation or recovery.

> ”The incubation period for COVID-19 is thought to [have] a median time of 4-5 days from exposure to symptoms onset.”
> -*Centers for Disease Control and Prevention (CDC)* (3)

> ”The time from exposure to symptom onset is thought to be three to 14 days, though symptoms typically appear within four or five days after exposure.”
> -*Harvard Medical School* (4)

"The mean incubation period and mean infectious period [are] 6 to 4 days and 3 days to 7 days, respectively."
-*The Lancet Public Health Journal* (5)

With this information, we can justify fixing γ to 0.2 ($\frac{1}{D_I} = \frac{1}{5} = 0.2$). By fixing γ we can focus specifically on the variability of β during different levels of nationwide policy. Note that ideally, if this project were more extensive, it would be beneficial to reproduce modeling with fixing gamma to a few different values (ie. 0.15, 0.2, 0.25).

$$\gamma = 0.2$$

For all modeling, mean squared error will be used to derive best fit recorded COVID19 data to the SIR model. Since γ is fixed, the optimization will only be finding the best variable value for the β infection rate. Additionally, the I(t) will be used as the estimator for the true number of infected individuals. It is also important to acknowledge the difference between 'cumulatively infected' and 'infected.' Number of infected, which is what we are concerned with, does not include those who have recovered.

$$\sum_{n=1}^{n} (\hat{I} - I)^2, \hat{I} = I(t)$$

First, to show that one β value cannot accurately fit the entire US COVID curve thus far, the below figure is a poor attempt at optimizing one β value to best fit the entire US covid curve. This does not work because β, again, changes with the implementation of policy and with the increased practice of social distancing.

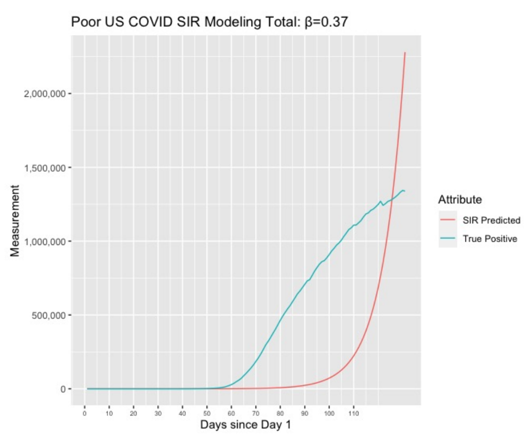

Figure 4: A POOR best fit of the entire COVID timeline

Clearly, trying to best fit the a SIR model with one fixed β value to all 140 days of COVID does not work due to β changing over time. Instead, one can much better fit the SIR model to true data from the different specified time periods discussed above. This is exhibited in the figures below.

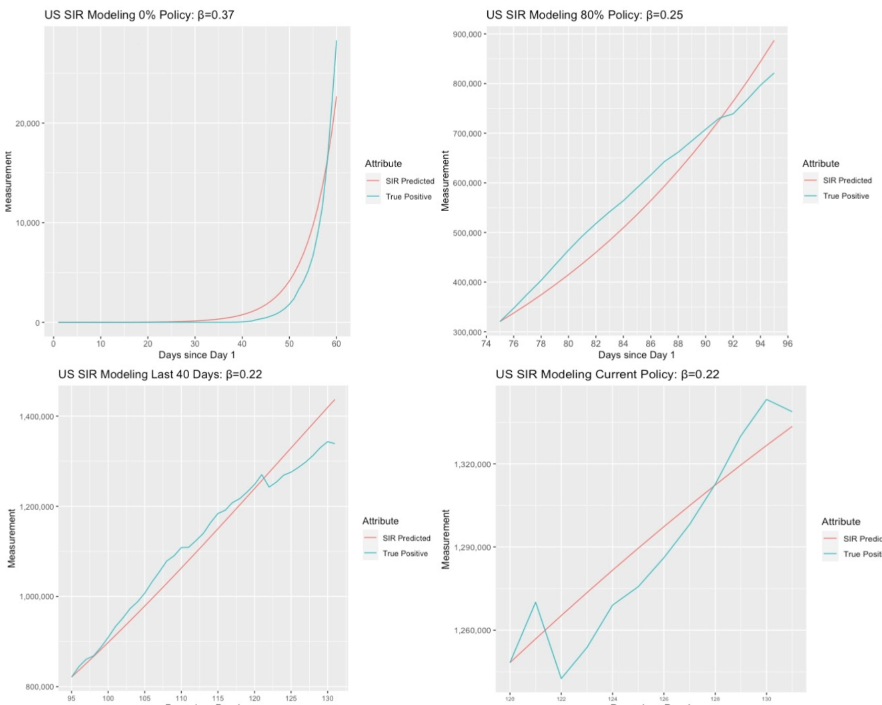

Figure 5: Best Fit Plots for β during varying periods of state distancing policy implementation (Day 1-60, Day 75-95, Last 40 Days, and Last 10 Days respectively

Using the standard errors of the above plots, we are able to derive the 95% confidence intervals for the beta values derived during each period of state policy implementation.

Beta Type	**Beta Value**	**95% Confidence Interval**
0% of State closures	0.370001260402868	[0.3700007,0.3700018]
80% of State closures	0.252043332390929	[0.2520433, 0.2520434]
Last 40 days	0.218785317537771	[0.2187852, 0.2187854]
Last 10 days	0.20789069334794	[0.2078906, 0.2078907]

Figure 6: Confidence Intervals for each modeled beta value

Again, the fact that these values may vary with slightly different fixed γ values should be considered, but the beta values would still have a downward trajectory over time regardless. We can plot the relative beta values over time in the US thus far.

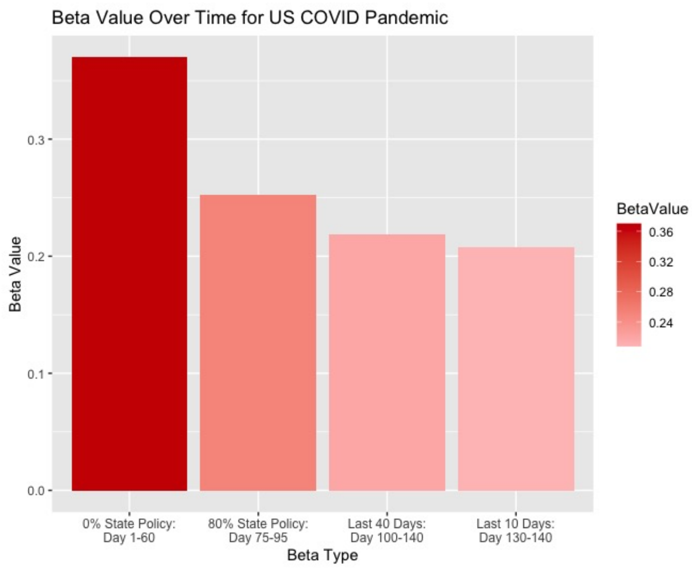

Figure 7: Beta Values over duration of US COVID Pandemic

One can clearly see that the β infection rate has declined significantly since the beginning of the COVID outbreak, meaning the effects of statewide distancing polices have dramatically decreased the number of potentially infectious interactions on a daily basis. Additionally, it is clear that we can attribute such a drop at least partially to statewide implementation of stay-at-home and Mandatory Closed Non-Essential Business orders on a national basis.

6 Future Consequences

A 0.37 β infection rate, which we saw during phases of no distancing policies in the US, compared to 0.20 β infection rate, which is our current beta rate after months of distancing policies nationally, may seem trivial. This is far from the case, though, as such a small difference has massive effects on the growth of the US COVID pandemic. Such massive effects are best exhibited through future COVID predictions based on the different β infection rates correlated with different levels of policy implementation.

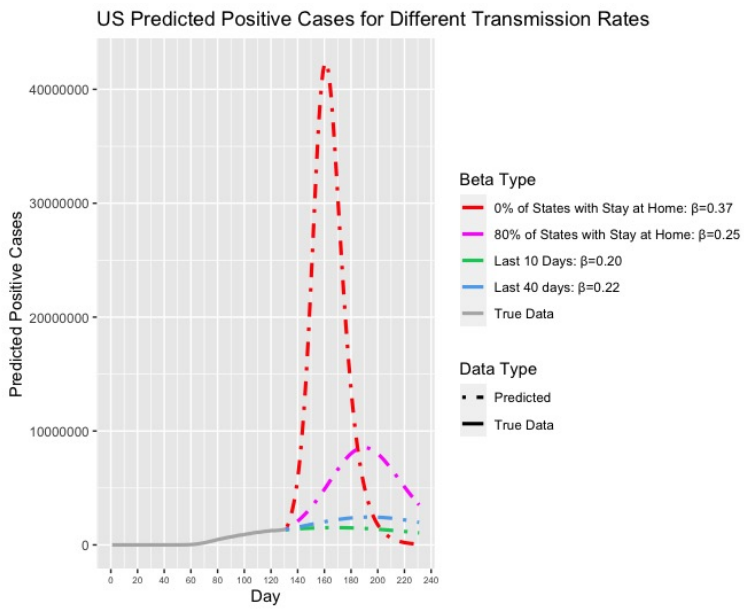

Figure 8: Predictions for COVID at different β infection rates

A β infection rate value of 0.37, which again represents β during periods of 0 percent state policy implementation, results in the predicted maximum number of positive cases being more than four times as large as if 80 percent of states enforced distancing policies. From the figure on transmission rates over time, it seems as if we have a declining transmission rate value. This is largely a result months of state policies for distancing on a national scale.

While the declining β transmission rate that we have documented thus far is encouraging, based on the data shown it likely will not continue. As shown in the original figure showing percent of states with policy implementation, the policies that have caused the US β transmission rate to decline are being slowly discontinued. Moreover, in the context of our current political condition, as mass protests of thousands of individuals gather in cities nationwide, we should consider the possibility of a massive spike in this transmission rate over the coming weeks(6).

What is worth considering, though, is that the transmission value will likely not return to the high value of 0.37 if state policy implementation drops back down to 0 percent. It will likely fall somewhere in between our highest calculated value and the lowest, as a lack of strict policy does not mean that there are not recommendations for distancing. Many states have neglected their stay-at-home policies, but have instituted 'stay-at-home recommendations' that many businesses and individuals follow anyway. These types of recommendations did not exist before policy was implemented. Thus, we should not see our transmission value return to quite as high as it was if states do choose to abandon the policies that have brought such beneficial drops to US COVID19 spread.

7 A Note on Assumptions and Potential Flaws

While the methodology used is somewhat sound, there are certain assumptions made, and also certain potential flaws. For example, by using percentage of states with policy implementation as a predictor of which time periods to use to predict beta values that represent the effects of social restriction, we weigh all states equally. While this does not mean our data has no significance, it could be detrimental to completely accurate results. There are many states in which the COVID epidemic has been significantly more tragic in than other states. Therefore the policy implementation in these states may have a much more significant effect on the nation as a whole than policy implementation in states that has less cases. The severity of the pandemic for each state, particularly in terms of cumulative positive cases, is shown in the figure below.

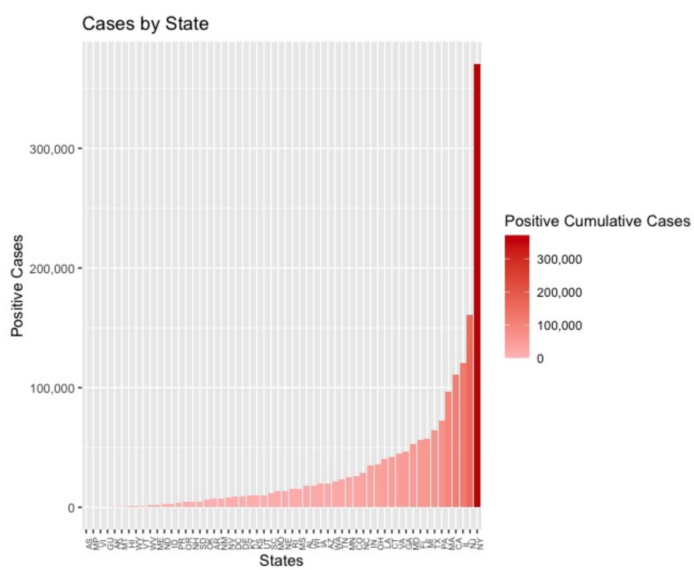

Figure 9: Severity of COVID outbreak in each state

The five states that have been most severely impacted by the pandemic in terms of total cumulative positive cases have the following policies in place currently.

- New York Stay-at-home Order, **NO** Closed Business
- New Jersey Stay-at-home Order, **NO** Closed Business
- Illinois Stay-at-home Order, Closed Business
- California Stay-at-home Order, **NO** Closed Business
- Massachusetts **NO** Stay-at-home Order, **NO** Closed Business

While four out of five of the states still have stay-at-home orders, one one has mandatory closed non-essential businesses. Since we have grouped these traits into one homogeneous policy variable, we may be missing some detrimental factors this may have. Also, as a result of not accounting for states individually, the percentage of policy implementation may be a less significant factor than implied by our data if severely impacted states are the ones neglecting to implement such policy. In this case, the beta values could be even higher, making policy implementation even more important to US recovery.

Moreover, some states are significantly more at risk than others due to the age demographics or high occurrences of medical traits that may have a causal relationship with serious illness due to COVID (ie. obesity, diabetes, heart conditions, etc). The percent of the population at risk of death in each state is represented in the figure below.

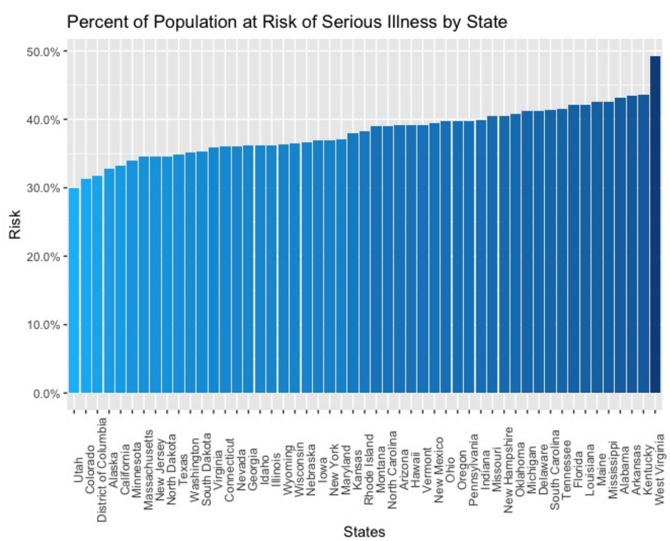

Figure 10: Percent of Population at Risk of Death in US States

The five states that are most severely at risk of high death counts due to the pandemic have the following policies in place currently.

- West Virginia **NO** Stay-at-home Order, **NO** Closed Business
- Kentucky **Never implemented a** Stay-at-home Order, **NO** Closed Business
- Arkansas **Never implemented a** Stay-at-home Order, **NO** Closed Business
- Alabama **NO** Stay-at-home Order, **NO** Closed Business
- Mississippi **NO** Stay-at-home Order, **NO** Closed Business

None of the states that are most at risk for serious illness from COVID currently have stay-at-home Orders or Business Closures. Some never even implemented them at all. This has slightly different consequences than the above case. Mainly, the death toll and total hospitalized cases due to COVID will be much higher than anticipated if this does not change.

One final flaw, particularly with future predictions, is that the SIR model is sensitive to the γ value that we assumed. If the value we assumed is slightly off from the true value, our predictions may be significantly off. On the other hand, our conclusions on the effect of distancing policies on β will be the same, so our overall paper conclusion will also remain the same.

8 Conclusion

Its easy to get caught up in the detriments of social distancing and the governmental policies enforcing it, whether they be economic or social. If nothing else, the data from this paper shows that the efforts of distancing have had, and potentially will have, a great effect on the prevention of COVID19 spread across the US. The downward trend of the SIR model transmission rate since the beginning of nationwide policy implementation is a massive indicator that such efforts should continue. With increasing occurrences of mass congregations of people and decreasing percentages of states maintaining mandatory policies in favor of distancing, we are becoming far more likely to see a reversal of this downward trend of transmission rate, and also increasingly likely to see a larger second wave of cases in the near future. Moreover, the discontinuation of distancing policies, or failure to ever implement them in the first place, in states that are have a population at high risk of death from COVID and states that have already been massively impacted by COVID will have a massive negative influence on the severity of the second wave.

References

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[4] Harvard Health Publishing. “Coronavirus Resource Center.” Harvard Health, Harvard Medical School, 1 June 2020, www.health.harvard.edu/diseases-and-conditions/coronavirus-resource-center.

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Note: All figures in this paper were made by me, and the R code for these figures can be accessed at the below link.

`https://docs.google.com/document/d/12W0puCpbdslGE2dMdExpyI25fHz8OCpX0dfImFZz_Bc/edit?usp=sharing`